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A Study of Aggregated 2D Gabor Features on Appearance-based Face Recognition

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Abstract

Existing approaches to holistic appearance based face recognition require a high dimensional feature space to attain fruitful performance. We have proposed a relatively low feature dimensional scheme to deal with the face recognition problem. We use the aggregated responses of 2D Gabor filters to represent face images. We have investigated the effect of "duplicate" images and the effect of facial expressions. Our results show that the proposed method is more robust than the PCA-based method under varying facial expressions, especially in recognizing "duplicate" images.

1. Introduction

Among the many body characteristics that have been used, face is one of the most commonly used characteristics and has been studied across a number of research fields, e.g. computer vision, pattern recognition [5],[8],[14],[15]. Face recognition is a non-intrusive method that captures still images and/or video sequences - from controlled, static environment to uncontrolled, cluttered environment; we can perform recognition using 2D images and/or 3D models with approaches that are holistic/global, or feature-based, or structural, or hybrid [16],[7].

In many commercial and civilian systems, since the environment is static and under control, full elasticity of the automatic face recognition system may not be required, i.e. with cooperative subjects, proper 2D frontal image can be obtained. In such a case, the automatic face recognition problem can be simplified to the classical pattern recognition/image retrieval problem, which deals mainly with feature extraction and identification/verification. Texture analysis is one of the main streams in image processing/analysis and retrieval, especially for monochromatic images. Characteristic textures contained in an image can be used to distinguish it.

The feature dimension of existing approaches are comparatively high, e.g. in [9]. We, therefore, suggested a holistic approach of relatively low feature dimension that exploits aggregated Gabor filter responses and distance measures to deal with the transformed face recognition problem.

The organization of the paper is as follows. Section 2 will review the background and outline the rationale of our suggested approach. Section 3 will discuss the results of our experiments. Section 4 will give our conclusion.

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2. Background and Proposed Method

We use aggregated 2D Gabor features, as a relatively low dimensional (space) representation of face because existing appearance-based face recognition techniques require a high dimensional feature space. Liu et al. [9], for example, reported that over 180 features were needed for the recognition using the FERET data set [13] containing 600 images (of 200 subjects) in order to attain similar performance of using 85 features with the ORL dataset containing 400 images (of 40 subjects). We therefore proposed a holistic approach with lower feature dimension to deal with the transformed face recognition problem; our proposed approach uses the mean and standard deviation of Gabor filters responses, which result from convolving 2D Gabor filters with grayscale face images, as features. Since Gabor filters of three scales and six orientations are adopted for feature extraction, feature dimension of the mean and the standard deviation of filter responses is thirty-six (eighteen each for real and imaginary part of filters' responses) each; that is there are totally seventy-two dimensions/features. Feature vector of a lower dimensional space can reduce the computation complexity, i.e. increasing speed, as well as the storage required for face recognition process.

L_p-norm are adopted as the (dis)similarity measures and the nearest neighbour rule with majority voting scheme helps to determine the best matched individual within the database.

2.1. 2D Gabor Filters

2D Gabor filters proposed by Daugman [3],[4] have been shown to be effective for texture analysis on monochromatic images. They optimally achieve joint resolution in space and spatial frequency; their orientations, radial frequency bandwidths and center frequencies are all tunable. Thereby, it is adopted to perform texture analysis. [2],[4],[9]

The expanded form of the family of Gabor filters used in our case study is

$$h(x,y,\omega,\theta)=\frac{1}{2\pi\sigma^2}\exp\left(\frac{-\omega}{8\kappa^2}(4x'^2+y'^2)\right)\left[\exp(\mathrm{i}\omega x')-\exp(\frac{\kappa^2}{2})\right] \quad (1)$$

for $\kappa=\sqrt{2\ln 2}\left(\frac{2^\delta+1}{2^\delta-1}\right)$ and $\omega=\frac{\kappa}{\sigma}$

where $\mathrm{i}=\sqrt{-1}$, ω is the radial center frequency, θ is the orientation of the filter, σ is the standard deviation of the Gaussian envelope and δ is the half-amplitude bandwidth of the frequency response [8].

3. Experiments and Results

We used the AR face database [11] from Purdue University in our experiments. The 13 images of each session are taken under various conditions: different facial expressions, illumination settings and occlusions (sunglasses and scarf). There is no limitation on the participant's clothes, make-up, ornaments, hairstyles, etc. [11],[9]. We conducted the experiment using the seven images without occlusion. A sample set of the fourteen preprocessed (warped) images used is shown in Figure 1. In Figure 1, the first row, i.e. (a)-(g), are images obtained in the 1st session (s1) and the second row, i.e. (h)-(n), are those obtained in the second session (s2). Our experiments conducted use only faces with facial expressions other than neutral, i.e. s1f: Figure 1 (b)-(d) or s2f: Figure 1 (i)-(k), as query images to match against a database that contains the seven images from either s1 or s2.

For cases 1 (s1f vs. s1) and 4 (s2f vs. s2), only images of 1st session or 2nd session are used, i.e. no unseen image is expected. For cases 2 (s1f vs. s2) and 3 (s2f vs. s1), however, either 1st or 2nd session is the registered set while

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the other one is the query set, i.e. matching "duplicates" [12]. We choose, for PCA, the same feature dimension as that of aggregated 2D Gabor features because we can determine the effectiveness of our proposed method directly from the system performance; we only use one feature dimensionality for PCA as it already captures over 99.75% of the total variability of the training sets (in either session of the two testing sets).

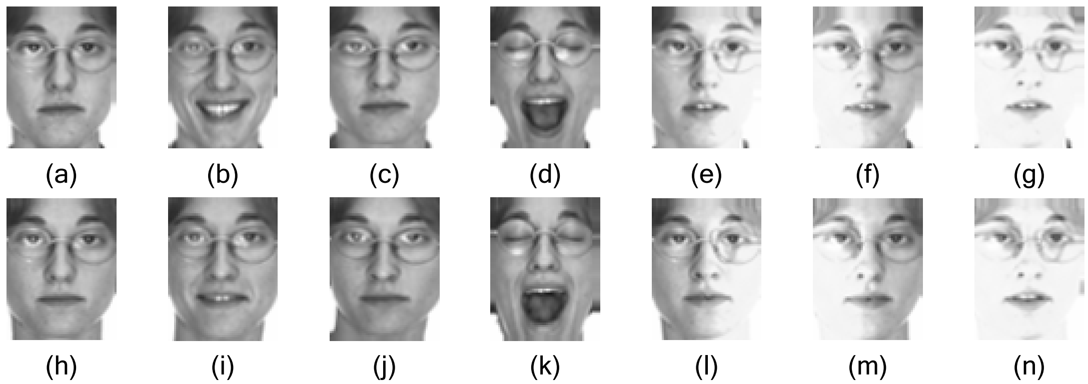

Figure 1 A set of warped images (a)-(g) are from 1st session while (h)-(n) are from 2nd session.

In our experiment, 50 randomly chosen subjects, which consist of 25 males and 25 females, were used. The facial features [10], such as the center of eyes, in each of the image are first localized. Then each face is aligned upright based on the center of eyes and the region containing the face is cropped to be of size 55×71. They are finally warped to a "standard" face [1] (see Figure 1). Afterwards, an oval mask is applied to remove the highly probable background area to extract only responses (for aggregated 2D Gabor Features) or pixels (for PCA) that are within the mask for feature extraction [12].

Table 1 Recognition rates using aggregated 2D Gabor features

	(Dis)Similarity Measure					
	L_1-norm			L_2-norm		
Image Sets	Worst	Average	Best	Worst	Average	Best
s1f vs. s1	33.33	79.33	100	33.33	78	100
s1f vs. s2	0	68	100	0	60	100
s2f vs. s1	0	66	100	0	60.67	100
s2f vs. s2	33.33	88.67	100	33.33	81.33	100

The k nearest neighbours chosen are $k = \{5, 10, 20\}$ but only $k = 5$ is shown as it always performs the best. The results (in %) of our proposed method and PCA are shown in Table 1 and Table 2 respectively. It is seen that our proposed method is more robust than PCA against variations in facial expression in all cases and similarity measures under consideration.

Table 2 Recognition rates using first 72 PCA coefficients

	(Dis)Similarity Measure					
	L_1-norm			L_2-norm		
Image Sets	Worst	Average	Best	Worst	Average	Best
s1f vs. s1	0	53.33	100	0	55.33	100
s1f vs. s2	0	45.33	100	0	45.33	100
s2f vs. s1	0	46.67	100	0	46.67	100
s2f vs. s2	0	53.33	100	0	54.67	100

4. Conclusion

We have proposed a relatively low feature dimension scheme for appearance-based face recognition. We derived an aggregated Gabor filter responses representation for face images that is of lower feature dimension. A comparative study on the effect of varying facial expressions, the effect of matching against "duplicates"

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and the effect of using different (dis)similarity measures, L_1- and L_2-norm has been carried out and reported for our proposed method, as well as for PCA as performance comparison. Our study on the influence of the facial expressions has shown that, PCA is not as effective as our proposed method whatever image sets (same or duplicate) or distance measures (L_1- and L_2-norm) we have been considered.

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